

## **Ensembles and Particle Filters for Ocean Data Assimilation**

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### **LONG-TERM GOALS**

It is our long-range goal to develop efficient methods for construction of error estimates based on the probability density functions of stochastic forecast models, and to apply those methods to the construction of practical data assimilation systems. We wish to understand in detail the mechanisms for propagation of uncertainty, and to investigate and devise new methods for quantifying the information content of forecasts and analyses.

Practical models of the ocean and atmosphere have typical state dimensions of  $O(10^5 - 10^7)$ , so direct calculation of the probability density function (pdf) is not practical. We must therefore apply Monte-Carlo methods, in which we draw ensembles, i.e., collections of samples drawn from the pdfs in question. In this context, the data assimilation problem becomes that of choosing an ensemble of points in state space drawn from the background, i.e., the “prior” pdf, and deriving a corresponding ensemble drawn from the “posterior” pdf, i.e., the pdf informed by observations. Data assimilation methods that use ensembles in the estimates of the prior and posterior pdfs are widely known as “particle methods,” since each ensemble member can be considered as a particle in state space. Since our long-range objective is the evaluation of the evolution of the pdfs of model state spaces, informed by observation, we will necessarily be concerned with particle methods.

### **OBJECTIVES**

Our principal objective is the development and evaluation of practical ensemble techniques for ocean data assimilation, and to quantify uncertainty in ocean analysis and prediction. Achieving our objectives will involve rigorous quantification of the information content of our models relative to the simplest estimates such as climatology or persistence, as well as quantification of the value added by new ensemble generation techniques and by the addition of new data sets to the analysis. To this end, we will explore all available methods for quantification of information content, including information theoretic methods, e.g., Haven et al. (2005) , Abramov et al., (2005).

### **APPROACH**

Data assimilation in its most general form is an exercise in conditional probabilities: the pdf that results from the assimilation process, the “posterior pdf,” is conditioned on the observations, considered as

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events that have taken place. If the system dynamics are nearly linear and all relevant pdfs are Gaussian, the process reduces to 4DVAR or the Kalman filter (e.g., Bennett, 2002). All such calculations rely on estimates of uncertainty, variability and error.

Utilization of all information contained in the observations is not possible even with highly detailed models, since the models cannot reproduce all physical sources of observed variability. We must therefore devise statistical models of the “representation error,” i.e., that part of observed variability that arises from sources neglected or not resolved by the model. Statistical models of representation error must be subjected to the same statistical tests as models of other sources of error. We have devised a method for estimating the statistics of representation error, based on a particular orthogonal decomposition of state space and observation space, in which we assign meaning to each orthogonal component (Richman et al., 2005; Richman and Miller, 2010).

As noted above, particle methods are the only practical way to work directly with the pdf of oceanic and atmospheric model systems. There are relatively few examples of application of particle filters to the ocean and atmosphere, e.g., van Leeuwen (2003), Dowd (2006). In these cases, very large ensembles were required to avoid the tendency of the assimilation process to lead to collapse of the ensemble to a single particle. Chorin and Tu (2009) proposed a promising method designed to avoid these difficulties. Initial tests of the method were performed on a common test problem from the engineering community.

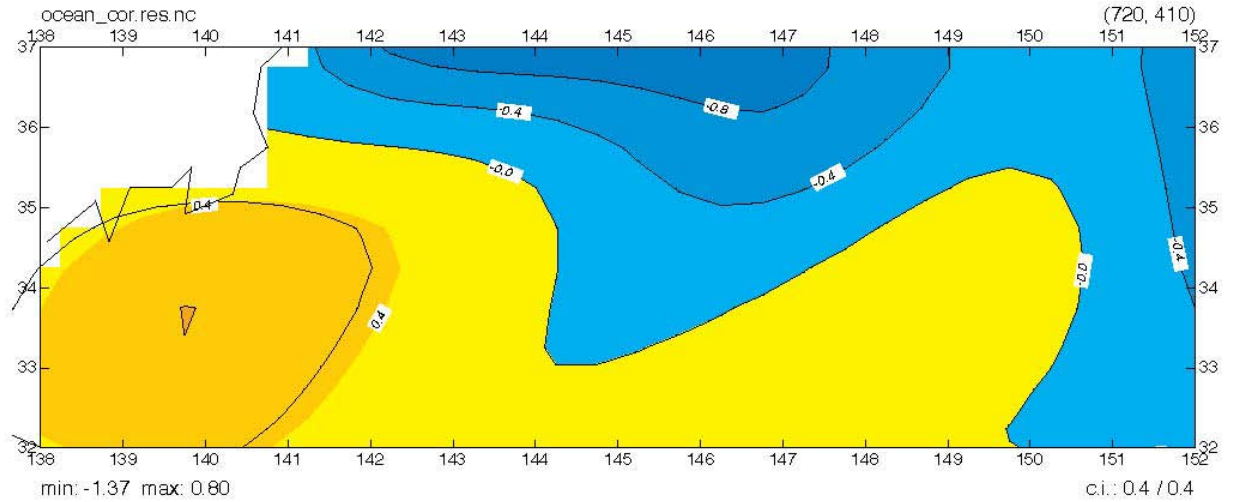
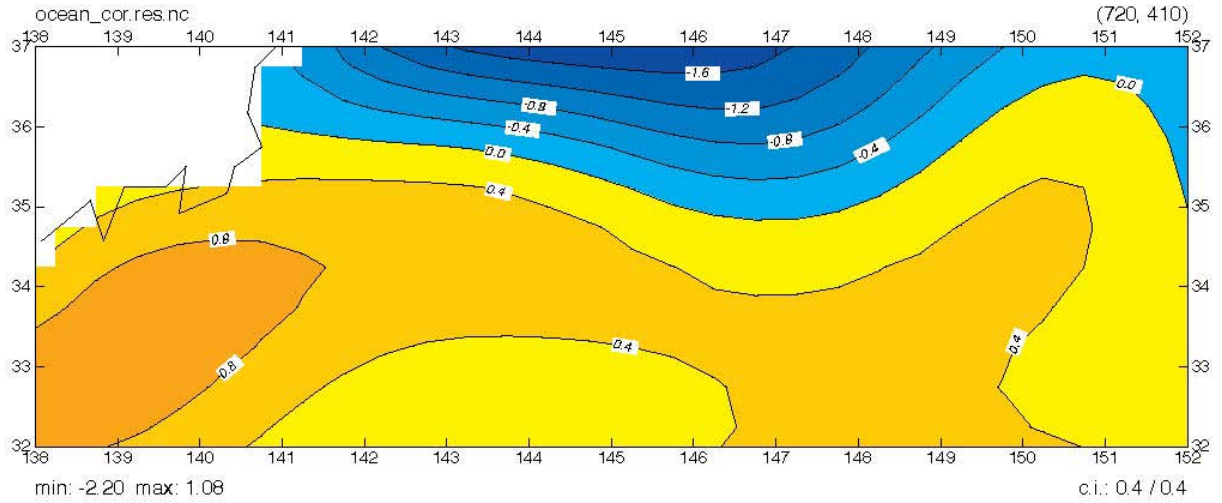
## **WORK COMPLETED**

We have implemented and evaluated an enhanced data assimilation system with the  $\frac{1}{2}^\circ$  version of MOM4 used as the ocean component of the NCEP operational climate forecasting system. The new data assimilation system includes our estimates of representation error.

We have implemented and tested the new particle method with simple nonlinear models, and modified the nearshore code of Kurapov et al. (2007) to the correct form for implementation of our particle method.

## **RESULTS**

Data assimilation schemes that do not account for representation error often have the effect of introducing structures into the analyzed state that are incompatible with model physics. This is illustrated in Figure 1, which depicts the analysis increments for the original and modified systems. In the original system, the data assimilation process imposes a temperature gradient of more than  $1^\circ\text{C}$  in less than a degree of latitude. This model cannot simulate such a narrow current, so the sharp SST gradient associated with the Kuroshio disappears in five days. The new system does not impose a sharp gradient that would be incompatible with model dynamics.



**Figure 1. SST analysis increments from original (top) and new (bottom) data assimilation systems, for April 23, 2003. The model is MOM4, implemented on a  $0.5^\circ$  global grid, with 40 levels in the vertical. The length of the assimilation cycle is 5 days. The sharp temperature gradient (top) imposed by the original analysis is not compatible with model physics, and disappears in 5 days, only to be restored again at the next assimilation time. The analysis increment imposed by the new system, though less faithful to the observed SST, is compatible with model dynamics, and the resulting analysis is less susceptible to initialization artifacts.**

The new particle method proposed by Chorin and Tu (2009) has been shown to be reliable in test cases.

## IMPACT/APPLICATIONS

Our promising new particle filter should lead to enhanced data assimilation systems and estimates of uncertainty, with implications for interdisciplinary and operational oceanography. Our work on Monte-

Carlo methods should provide enhanced capability for evaluation of forecasts of the ocean and atmosphere, in addition to application to data assimilation.

Our work on estimation of representation error statistics and statistics of model error that take physical model limitations into account should lead to new efficient ensemble generation methods in two ways. Ensembles of model forecasts informed by the ability of the model to represent physical variability can be constructed, as can ensembles of simulated representation error fields generated by stochastic models of representation error (cf. Richman et al., 2005, Richman and Miller, 2010). Ensembles of model forecasts, combined with ensembles of simulated representation error can be combined to provide fields of simulated data suitable for OSSEs or for interdisciplinary modeling and data assimilation.

## TRANSITIONS

We are working with scientists at NCEP to begin the process of incorporating our error estimates into their operational climate forecast system.

## RELATED PROJECTS

Estimating the representation error of satellite and in-situ data for data assimilation into ocean models.

Particle Filters and Ecological Models (PFEM): Application of chainless Monte-Carlo methods to mapping the ecology of the North Pacific Ocean

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## **PUBLICATIONS**

Richman, J. G. and R. N. Miller, 2010: Estimating Representation Error for Ocean General Circulation Models. *J. Atmos. Ocean. Tech.*, submitted.